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Climate-smart agricultural practices and welfare of rural smallholders in Ethiopia: Does planting method matter?☆

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ABSTRACT

The purpose of this study is to provide empirical evidence on the impact of a climate-smart agricultural practice (row planting) on the welfare of rural households. Data collected from 260 households in Gubalafto woreda of Amhara region in Ethiopia were analyzed using Propensity Score Matching (PSM) and a Semi-parametric Local Instrumental Variable (LIV) version of the generalized Roy model. The results from the PSM model revealed that adoption of row planting technology has a positive and significant impact on per capita consumption and on crop income per hectare. Covariates are well balanced and the impact estimate is insensitive to unobserved selection bias indicating that the estimates are a pure effect of the row planting technology. Marginal benefit of row planting is increasing with higher propensity of the farmer to adopt the climate smart planting technology. Therefore, scaling up the technology will significantly contribute to farmers' resilience against the adverse effects of climate change through enhancing household's income and food security.

1. Introduction

Climate change affects millions of people living in sub-Saharan Africa by reducing crop yield, food security and overall welfare of rural households (Endalew et al., 2014; Campbell et al., 2016; Lewis, 2017). Food insecurity has been a serious challenge for Ethiopia for several decades. Some of the main drivers of food insecurity in Ethiopia are low agricultural production, frequent drought, environmental degradation, rural-to-urban migration, growing population, and scarcity of arable land (WFP, 2013; Minten et al., 2013; Lewis, 2017). More than 85% of Ethiopia's population depends on agriculture for their livelihood. The sector depends on rain fed agriculture and features high poverty, subsistence production, poor infrastructure, loss of soil fertility, and low productivity (Sibanda et al., 2017).

Against this background, one of the pillars of the Climate Resilient Green Economy (CRGE) strategy of Ethiopia, which was launched in 2011, is to improve agricultural production practices for better food security and farmer income while reducing emissions from the sector. This calls for the adoption of yield enhancing climate smart agricultural practices (CSA) to tackle the challenges of low agricultural productivity and the threats posed by higher weather variability and vulnerability to climate change. Adoption of CSA practices aims to sustainably increase agricultural productivity and incomes and hence build resilience against shocks, including adverse effects of climate change. Climate smart agriculture has a potential to reduce poverty and food insecurity in developing countries through increasing agricultural production and incomes of rural households (Nyasimi et al., 2014; James et al., 2015; Food and Agriculture Organization (FAO, 2016; Teklewold et al., 2017). However, quantifying the impacts of these innovative practices requires rigorous study in order to inform policy makers about the magnitude of the impact and the potential to improve the welfare of rural farming communities. Climate-smart practices range from the farm level to international policy and financial mechanisms. This study focuses on one of the farm level climate smart agricultural practices: row planting of teff in rural Ethiopia.[1]

The possibilities to achieve an African Green Revolution through technological change, research and development efforts have led to the development and release of a number of improved crop varieties and production techniques. It is widely believed that this led to substantial yield gains observed in the 1980s through the 1990s (Simtowe et al.,

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[1] Row planting is labor intensive (Vandercasteelen et al., 2014; Dinku and Beyene, 2019) CSA practice. Similarly, there are CSA practices which are labour intensive (see for example, Milder et al., 2011).

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2012; Nin-Pratt and McBride, 2014; Stewart et al., 2016). However, the conventional Green Revolution agricultural development approach was not successful in many parts of Africa (Milder et al., 2011).The main drawback was that the Green Revolution was not designed to be climate resilient and hence could not achieve food security. In addition, it is highly capital intensive and rely on external inputs which is the key for the success of the program in increasing productivity (Pingali, 2012).[2] With growing focus on the effects of climate change, climate-smart agricultural practices have been identified in Africa, with the capacity to increase productivity and build resilience (James et al., 2015).Currently, adoption of high yield variety seeds and improved production technologies is on the top of the Ethiopian government's agenda for the successful achievement of its five-year Growth and Transformation Plan (GTP). However, their wide-scale adoption remains a challenge, especially among smallholder farmers.

Despite the release of different improved varieties, several farmers are still planting the improved varieties in a traditional way (broadcasting method). In recent years, the Government of Ethiopia, through the Agricultural Transformation Agency (ATA), rolled out a nationwide campaign to promote row planting for teff production, aiming to scale up adoption to about 2.5 million farmers. Anecdotal evidence suggest that row planting is superior to the traditional way of planting seeds. Most empirical evidence on the extent to which this technology is superior to the traditional method of sowing seeds is qualitative (e.g. Unique-Kulima, 2017; Fayso, 2018) or based on agronomic evidence (e.g., Asargew et al., 2015; Abraha et al., 2016). Therefore, the objective of this study is to estimate the welfare impact of row planting agricultural technology on rural smallholder farming communities in Gubalafto woreda[3] of the Amhara region, using a Propensity Score Matching and a semi-parametric Local Instrumental Variable (LIV) method. We estimate the impact of row planting of the Quncho[4] teff variety on the welfare of rural smallholder farmers, which is measured in terms of consumption expenditure[5] and crop income of teff per hectare. Empirical evidence on these new agricultural practices will help fill knowledge gaps in the areas of climate-smart technology adoption.

The literature on the effects of climate-smart agricultural practices is very scant in developing countries like Ethiopia. Based on a pilot study in Kenya, Mutoko et al.(2015) conclude that inadequate farm labor, lack of adequate knowledge, unavailability of seeds, and lack of funds to implement some of the improved practices are the major constraints to the adoption of CSA practices. Similarly, Williams et al. (2015) have indicated that socioeconomic factors such as labor are among the main challenges or constraints for the adoption of CSA. Most empirical studies of agricultural technology adoption in Ethiopia have focused on practices other than the method of sowing (improved seeds, fertilizer, soil and water conservation, minimum tillage, etc.; see Kassie et al., 2010; Teklewold et al., 2013; Tekelewold et al., 2017; Beyene et al., 2017).To the best of our knowledge, there are few studies on ex-post impact assessment of adoption of row planting particularly of teff in Ethiopia(e.g.,Alemu et al., 2014; Vandercasteelen et al., 2018).A recent study by Vandercasteelen et al. (2018) found that row planting did not significantly increase teff yield. On the other hand, Alemu et al (2014) argue that the impact of wheat row planting depends on agro-ecology; they found it has a positive impact in the highlands and no significant effect in the lowlands.

Therefore, this study aims to provide rigorous empirical evidence on the impact of row planting on two outcome indicators: crop income per hectare and consumption by farming households. The study adds to the literature by analyzing the impact of row planting technology on an improved teff variety. Given that teff is one of the staple crops in the country in general and in the study area in particular, this empirical impact assessment study can inform policy makers and stakeholders about the effect of the practice on the welfare of rural farming communities.

2. Overview of teff production and varieties in Ethiopia

Teff is the most significant food crop (in terms of both area and value) produced by Ethiopian farmers. It is estimated that over one-fifth of the total cultivated area is covered by teff, which is grown by 6.3 million farmers (Minten et al., 2013). Two out of three Ethiopians consume teff daily. It is a staple food for over 50 million people and occupies the largest place in the grain market (Tareke, 2009; Minten et al., 2013).

Teff is becoming a world crop due to its health benefits as it is gluten free and therefore important for those who suffer from gluten intolerance or celiac disease (Dekking and Koning, 2005).It is second only to maize in production and consumption in Ethiopia. Teff is mainly produced in the Amhara and Oromia regions, together accounting for almost 88% and 86% of the total production and area covered by teff, respectively in the country (Lee, 2018).

Compared to other cereals, teff is a relatively low risk crop as it can withstand adverse weather conditions. In addition, the crop suffers from relatively few disease and pest problems, and can grow under water-logged conditions. Teff can grow under wide and diverse agro-ecologies. Even though there are areas where the crop is grown during the short rainy season (Belg), teff is mainly cultivated during the main rainy season (Meher). It grows best between altitudes of 1800 and 2100 m with an annual rainfall of 750–850 mm and a temperature range of 10–27 degrees centigrade, though it can also grow in much more varied areas with rainfall up to 1200 mm. Improved varieties of teff and production techniques are increasingly becoming popular in major teff growing areas of Ethiopia, though adoption is currently limited.

Despite the significance of the crop in terms of both production and consumption, yields are relatively low (around 1.2 t/ha), which is lower than the average yields of other cereal crops: maize (3.1 t/ha), rice (2.8 t/ha), and wheat (2.1 t/ha). In addition, high loss rates (25–30% both before and after harvest) reduce the quantity of grain available to consumers by up to 50% (Fufa et al., 2011).

The majority of planting in Ethiopia currently is done by hand-broadcasting, which not only uses significantly more seed than more modern methods, but also produces significantly lower yields. Row planting, by contrast, is a climate-smart agricultural practice which is preferable for spacing, requires less seeds, and makes it easy to weed, harvest and control pests and diseases, ultimately increase production significantly (Okiror, 2016). The use of mechanized planting technologies (such as row planters) increases yield by using the correct seed rates and evenly spacing seeds (ATA, 2013).By reducing the seed rate from 30Kg to 5 Kg per hectare and planting in rows, rather than the traditional broadcasting method, teff plants thrive better due to reduced competition for water, sunlight and soil nutrients. Each plant yields more stalks and more grains per stalk, which, when combined with the savings on inputs (seeds), leads to even higher potential net profits.

In 2011, the ATA's teff program started supporting on-farm productivity enhancement demonstrations, including new teff planting technologies and practices, such as row planting, reduced seed rates, and transplanting techniques. Beginning in four regions with 1400

[2] We thank one of the referee for pointing out this shortcoming of the green revolution.

[3] Woreda is a district and are the third level administrative divisions of Ethiopia, managed by a local government. It consists of Kebeles, which is the smallest administrative unit in the country

[4] The Quncho teff variety is very common in the study area and almost all the farming communities grow this type. Focusing on this variety helps us estimate the true impact of the planting method.

[5] Here the consumption expenditure refers to total consumption expenditure per adult equivalent, i.e., the total household consumption expenditure is divided by the household size, which is in adult equivalent scales.

farmers at 90 Farmer Training Centers (FTCs), these demonstrations proved that yields can be increased up to 75%, on average, with some exceptional farmers producing up to 5 tons/ha.

Adoption of climate smart agricultural practices reduces food insecurity which has been a serious challenge for Ethiopia for several decades. Some of the main drivers for food insecurity in Ethiopia are low agricultural production, frequent drought, environmental degradation, rural-urban migration, demographic pressures and so on (WFP, 2013; Lewis, 2017). Against this background, one of the pillars of the Climate Resilient Green Economy (CRGE) strategy of Ethiopia, which was launched in 2011, is to improve agricultural production practices for better food security and farmer income while reducing emissions from the sector. This directly calls for the adoption of yield enhancing climate smart agricultural practices. Given the scarcity of suitable arable land and the rapidly growing population, Ethiopia will need to scale-up the adoption of yield-increasing technical innovations to ensure continued agricultural growth and to safeguard national food security (Minten et al., 2013). As part of these efforts doubling both the grain and the straw yield of teff would significantly contribute to Ethiopia's economy and food security. Hence empirical studies of this sort have important role in tracking the implementation processes of national policies of Ethiopia, i.e., implementation processes of the GTP and CRGE.

3. Data and the study area

This study was conducted using household level survey data collected in the northern part of the country, Amhara region, Gubalafto Woreda (also known as district). Gubalafto district has a total population size of 176, 492 (Central Statistical Agency (CSA, 2017) of which 96%are rural households whose livelihood depends on agriculture (Central Statistical Agency (CSA, 2017). Gubalafto Woreda has four agro-ecological zones: lowland (Kola), mid-altitude (Woinadega), highland (Dega) and to some extent Wurch.[6] The most commonly produced crops in this woreda are annual crops such as teff, sorghum, maize, chick pea, haricot beans, horse bean and cash crops like onion and pepper. It is selected as a study site because teff is the dominant cereal crop produced in the area and there are substantial numbers of users of improved teff seed variety with row planting technique, following a recent intervention by the government.

In Gubalafto woreda, kebeles [7] (villages) which are considered to be the best producers of teff are selected: Woinye, Geshober, Beles, Anova and Gedo. Four of these five kebeles (except Gedo) are considered for this study. To this end, multistage sampling procedure is employed to select 260 Quncho teff producing households.[8] To facilitate good matching, it is advisable to have a larger control group than treated individuals (adopters of the technology) among the sample households. Accordingly, 104 adopters and 156 non-adopters are selected. In the first stage, Quncho teff producing farmers are purposively selected in the study area. The second stage involves the stratification of the farmers into two groups, consisting of adopters of row planting technology of Quncho teff variety and non-adopters. Non adopters are Quncho teff producers using broadcasting planting method. The third stage is random selection of teff producing farmers from each category of treatment status in each kebele. The sample size in each kebele was determined proportionately based on the size of the population. The survey was conducted in September 2013.Data from a sampled household was gathered through face to face interviews using a structured questionnaire. The structured questionnaire contains information on household's socioeconomic characteristics such as age and sex of household head, level of education, family size, etc., use of inputs such as fertilizer and improved seeds, production of teff on each plot of farmer's land, and perception of the new row planting techniques. In addition, information on social capital such as membership in farmers' association, amount and source of income, and details of consumption expenditure were gathered during the survey (Fig. 1).

4. Empirical approaches

The greatest challenge in evaluating any intervention or program is obtaining a credible estimate of the counterfactual: what would have happened to participating units if they had not participated? Therefore, identification of the counterfactual is the pillar of a valid impact evaluation (Heinrich et al., 2010).If treatment is randomly assigned, the outcome of untreated individuals can be a good estimate of the counterfactual. However, if households that are treated have characteristics that differ from the ones that are not treated, comparison of the outcome between the two groups will yield biased estimates (Anderson et al., 2009). Without information on the counterfactual, the next best alternative is to compare outcomes of treated households with those of a comparison group that has not been treated. In doing so, one attempts to pick a comparison group that is very similar to the treated group, such that those who received treatment would have had outcomes similar to those in the comparison group in the absence of treatment (Khandker et al., 2010).

Based on Heckman et al. (1998) and Smith and Todd (2005), let Y_1 be the mean of the outcome variable in the treatment group (row planters) and Y_0 the mean outcome of the control group (broadcasters). The impact of participating in row planting () is given by,

$$\tau = Y_1 - Y_0$$

The main challenge of this evaluation is that both the treatment and control outcomes cannot be observed for the same individual at the same time, that is, the treatment indicator is either 0 or 1. Literature on program evaluation calls this a missing data problem (Smith and Todd, 2005). Average treatment on the treated (ATT), which focuses on the impact of row planting on those for whom the intervention is introduced, is the most common evaluation parameter.

In random program assignment, the average effect is estimated by taking the difference in means of the outcome variable between the treatment and control group (Heckman et al., 1998).

This procedure cannot be applied for our case since row planting program is a non-random process. The ATT is given by:

$$\tau_{ATT} = ATT(\tau X; Z = 1) = E(Y_1 - Y_0) = E(Y_1, Z = 1) - E(Y_0, Z = 1),$$

Where Z is the treatment indicator variable showing whether the household received treatment or not: Z_i is equal to 1 if the household is row planter; 0 if broadcaster. X represents control variables. Data on row planters identify the mean outcome in the treated group $E(Y_1, Z = 1)$. The mean outcome in the untreated $E(Y_0, Z = 1)$ is not observed and a valid substitute has to be chosen to estimate ATT. Since the row planting program followed a non-random process, we applied suitable non-experimental methods. Therefore, we use propensity score matching which helps to mimic randomization of the assignment of households and estimate the effect of row planting.

Finally, a covariate balancing test is required after matching to make sure that the differences in the covariates in the two groups of matched samples are eliminated for the matched group to be a plausible counterfactual (Ali and Abdulai, 2010). Among different versions of balancing tests, the most widely used balancing test is the mean absolute standardized bias between adopters and non-adopters suggested by Rosenbaum and Rubin (1983). They recommended that a standardized bias difference of greater than 20% should be considered too large and an indicator of failure in matching.

Propensity score matching is not strong in capturing the effects of unobserved heterogeneity. To complement the findings of PSM, a semi-parametric local instrumental variable (LIV)version of the generalized

[6] Wurch is a traditional term for areas above 3800 meters above sea level.
[7] Kebele is the lowest administrative unit in Ethiopia.
[8] We determined the sample size based on resource availability.

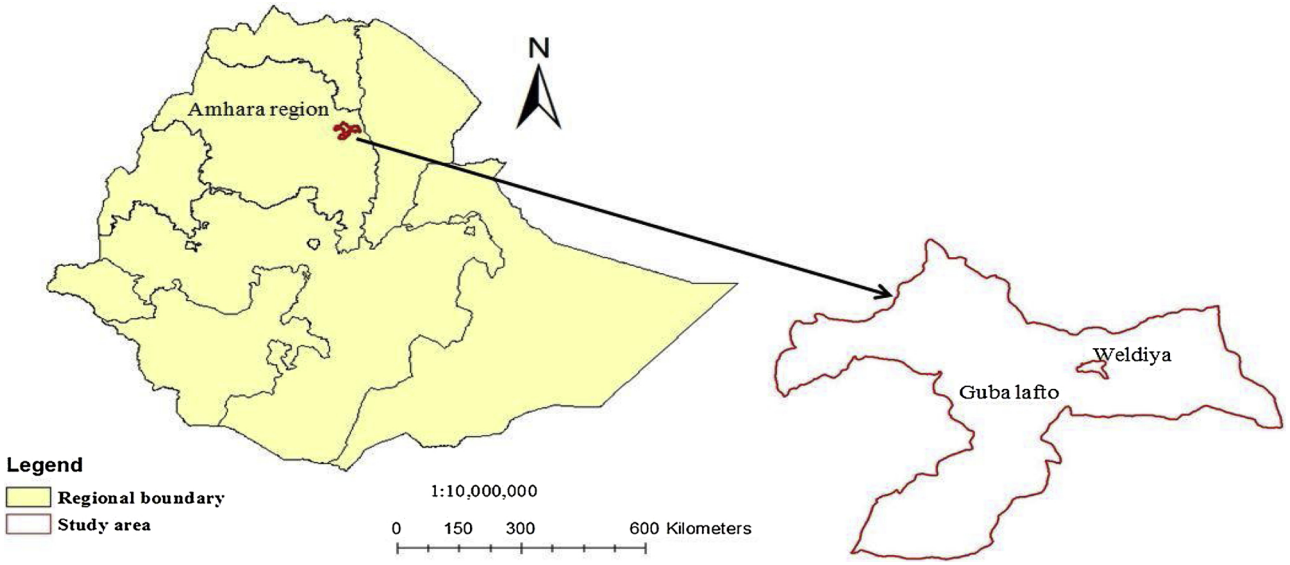

Fig. 1. Location map of the study area.

Roy model is used to estimate both the marginal treatment effect and average treatment effect given selection on unobservables and selection on returns.[9] We followed Brave and Walstrum (2014) for the semi-parametric LIV model. Unlike linear regression with endogenous treatment effects and maximum likelihood estimation of switching regression, the marginal treatment effects model produces both the marginal treatment effect and average treatment effect of the adoption decision using both parametricand semi-parametric methods (Brave and Walstrum, 2014).

5. Results and discussion

5.1. Descriptive statistics

The variables included in this study were selected based on related literature. The summary of variables used in the empirical analysis is presented in Table 1 below. Of the total sample households, 40% of them planted and produced Quncho teff using the row planting method in the 2012 cropping season. About 89% of sample households are male headed and there is no significant difference in mean of sex composition between adopters and non-adopters. As described in Table 1, some socioeconomic variables show significant mean variation between adopters and non-adopters of the new planting technology. Variables such as education, mobile phone ownership, livestock ownership and income from the production of other crops are significantly different (5% level) between adopters and non-adopters. Similarly, the mean values of the variables household size, ownership of radio/television, number of oxen owned, contact with government extension agents, membership in farmers' association, distance to the main road and non-farm income are significantly different (at the 1% significance level) between adopters and non-adopters of row planting technology.

Adopters of the row planting technology are more likely to be male headed, younger, more educated and with higher household size compared to non-adopters. The average educational level of the household head for adopters and non-adopters is about 4 and 3 years, respectively. Better educational level facilitates farming household's use of new agricultural technologies (Rahm and Huffman, 1984; Abdulai and Huffman, 2005).

Compared to non-adopters, adopting households have higher ownership of mobile phones, oxen and other livestock, and radio/television. It is believed that better endowment of information sources, higher income and better access to credit institutions helps farmers to adopt new farming technologies. The average household size for the sample households is about 4 people, which is lower than the national average of 4.7 (Ministry of Health (MOH, 2011). The average farm size of households is 0.45 ha and there is insignificant difference in land holdings between adopters of row planting (0.454 ha) and non-adopters (0.453 ha). The mean non-farm income of row planting households and broadcasters is 4050 and 1599 Birr, respectively, which is statistically significant. The average income obtained from the production of other crops is about 5776 and 7186 Birr for broadcasting households and row planters, respectively.

The other important variable is the outcome variable of interest which is per capita consumption.[10] There is a significant difference in per capita consumption expenditure between the two groups of households (i.e. adopters and non-adopters). The average per capita consumption of row planters and broadcasters equals 7765.36 and 6077.66 Birr, respectively. Crop income per hectare[11] is the other welfare indicator used in this study. The mean crop income per hectare of row planting households equals 8970.77 Birr and for broadcasting households it is 7678.369 Birr with a significant difference(at the 10% level).

Sample farming households were asked about their perception of row planting technology. Adopting households were asked why they use row planting production technology. Accordingly, 96% of adopting households responded that better productivity of the technology is the main reason for adoption. The second most important reason for using row planting technology is no lodging (81%). Lodging is the falling over of the crop during its time of maturity which negatively affects the crop yield. Since teff has tall, tender stems which can easily fall over, it is the most common problem for farmers, especially those who produce teff

[9] The problem of selection on returns happens when the adoption decision of row planting and unobserved variables are essentially related (essential heterogeneity) which affects the return of the adoption (outcome variables) and it is this dependence that makes it relevant to examine the marginal effect of adoption of the row planting.

[10] To get the monetary value of per capita consumption, the current market price (i.e. survey period) in the local market for each food item is used.

[11] In the calculation of crop income per hectare, the per kilo value of teff is calculated and multiplied by the total amount of yields in terms of kilograms produced. 16 Birr/kg is the market price of teff at the time of the data collection.

Table 1
Summary of descriptive statistics of sample households.

Variable name	Non-adopters (n = 156) Mean (SE)	Adopters (n = 104) Mean(SE)	Diff (= mean of NA-Mean of Ad)
Age of household head	49.76 (1.17)	47.8 (1.07)	1.94
Gender of household head (1 if male, 0 if female)	0.87 (0.027)	0.91 (0.028)	−0.04
Education of household head (in years)	3.09 (0.279)	4.05 (0.33)	−0.958**
Household size (adult equivalent)	3.67 (0.88)	4.32 (0.129)	−0.66*
Ownership of radio/television	0.59 (0.04)	0.76 (0.042)	−0.17*
Mobile ownership (1 if the household has mobile phone, 0 otherwise)	0.69 (0.037)	0.82 (0.038)	−0.125**
Number of oxen owned	1.02 (0.05)	1.28 (0.06)	−0.26*
Other livestock ownership (TLU)	0.58 (0.048)	0.65 (0.056)	−0.068
Application of pesticides (yes = 1, 0 otherwise)	0.48 (0.04)	0.54 (0.05)	−0.051
Contact with government extension (1 if there is contact, 0 otherwise)	0.78 (0.033)	0.99 (0.010)	−0.21*
Income from other crops (in ETB[++])	5976.20 (347.97)	7186 (523.80)	−1210.1**
Access to credit (1 if yes, 0 otherwise)	0.846 (0.029)	0.90 (0.029)	0.058
Membership in farmers' association (= 1 if member, 0 otherwise)	0.74 (0.035)	0.90 (0.029)	−0 .16*
Distance to the main market (in minutes)	53.95 (2.83)	54.80 (2.56)	−0.86
Distance to extension office (in minutes)	33.95 (2.2)	32.58 (1.88)	1.36
Distance to the main road (in minutes)	44.45 (3.23)	29.94 (2.71)	14.50*
Soil and water conservation (= 1 if yes, 0 otherwise)	0.91 (0.023)	0.97 (0.016)	−0.06***
Non-farm income (in ETB)	1599.62 (335.2)	4050 (702.2)	−2450*
Farm size (in hectare)	0.453 (0.016)	0.454 (0.017)	−0.001

Note: The numbers in parenthesis are the standard errors. *, **, and ***, represent level of significance at 1%, 5%, and 10% level, respectively.
[++] ETB (Ethiopian Birr) and1 USD = 18.3 Ethiopian Birr at the time of the survey in 2012.

using the traditional planting method (broadcasting). Row planting therefore reduces lodging and enhances productivity. In addition to this, the benefits in terms of lower seed rate (74%), less fertilizer requirements (59%), less erosion (39%), and lower weeding cost (13.4%) are believed to be the major reasons for using the row planting technology. Planting in rows reduces the seed rate from 30 kg to 5 kg per hectare compared to the traditional broadcasting method. Since there is reduced competition for water, soil nutrients and sunlight due to reduced seed rate, the teff plant thrives better and gives better yield.

The non-adopters were asked why they use the traditional broadcasting method rather than row planting. The majority of non-adopters (92%) responded that they did not use row planting since it is labor demanding. This shows that there is a need to think about less labor intensive technology in order address the labor shortage problem of some households and enhance the take up rate of the technology. In addition, about 18% of non-adopters did not believe that row planting would give better yield than the traditional broadcasting method. The other reasons for not using row planting technique were time consuming (46.7% of non-adopters), and lack of awareness about the technology (23.7%). This may suggest that better information about the technology could influence non adopters to adopt the technology.

5.2. Estimation of propensity score and matching

Estimating the propensity score is important for two reasons. The first one is to estimate the average treatment effect on the treated (ATT).The second is to obtain matched treated and non-treated farming households. Logistic regression is used to estimate the propensity scores.

5.2.1. Estimation results of the determinants of adoption

The results of the logit estimates of row planting technology of Quncho teff and the covariates that are used in the matching process are reported in Table 2. The overlap condition was also imposed and the balancing property was set and satisfied. Among row planters, the predicted propensity score ranges from 0.0767 to 0.979 with mean of 0.54, while among broadcasters, it ranges from 0.0023 to 0.912 with a mean of 0.31. Thus, the common support condition is satisfied in the region of [0.0767, 0.979] with a loss of 34 observations (about 13% of the total sample) from non-adopters of row planting technology. The model has pseudo R^2value of 0.194 and log likelihood value of -141.The coefficients of most of the variables have the expected signs and they include covariates like household size, ownership of radio, contact with government extension agents, and distance to the main road, among others. The coefficient for family size which is used as a proxy for labor availability in the household is positive and significant at 1%. Higher household size implies higher availability of labor which can facilitate the adoption of agricultural technology. A recent study by Dinku and Beyene (2019) also argue that family size is positively correlated with the adoption of row planting of wheat in Ethiopia. Ownership of a radio has a positive impact but not significant As expected, the more contact a household has with government extension agents, the easier it would be to access information about technology, and hence it is positively and significantly correlated with adoption of row planting. Non-farm income is another important variable affecting adoption positively and significantly. With higher non-farm income, farmers become risk takers and adopt new technology (Ayinde, 2008). Hence, non-farm income can augment a household's income and can influence a household's adoption decision and consumption expenditure.

Table 2
Estimation of the logit model.

Variables	Estimates
Age of household head	−0.0078 (0.014)
Sex of household head	−0.1020 (0.503)
Education of household head	0.0340 (0.533)
Household size	0.440*** (0.136)
Ownership of radio/television	0.542 (0.326)
Mobile ownership	−0.0286 (0.374)
Contact with government extension	3.17*** (1.052)
Number of oxen owned	0.2965 (0.282)
Livestock ownership(TLU)	−0.2834 (0.286)
Income from other crops	0.00002 (0.000)
Access to credit	0.6741 (0.457)
Membership in farmers' association	0.0657 (0.471)
Distance to extension office	0.0009 (0.007)
Soil and water conservation	0.960 (0.7543)
Non-farm income	0.0001** (0.000)
Pseudo R2	0.19
Number of Observation	260

***, ** refers to level of significance at 1%, and 5%, respectively.

The sample differences in the raw data (unmatched) significantly exceed those in the samples of matched cases. Hence, the process of matching creates a higher degree of covariate balance between row planters and broadcasters. In addition to the standardized bias measure,

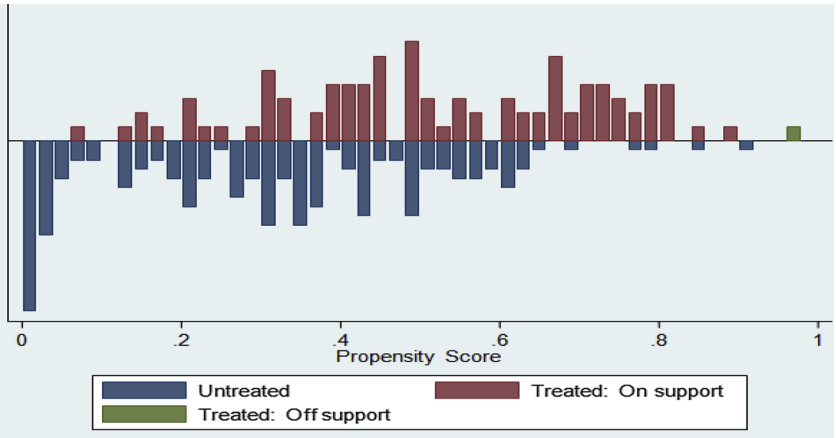

Fig. 2. Propensity score distribution and common support for propensity score estimation.

we used other balancing indicators, such as the likelihood ratio test of the joint significance of all covariates and the pseudo R^2 from the logit of treatment status on covariates before matching and after matching on matched samples (Caliendo and Kopeinig, 2005). After matching, there should be no systematic differences in the distribution of covariates between the two groups, and hence the pseudo R^2 should be fairly low and the joint significance of all variables should be rejected. Therefore, the distribution of covariates after matching, the low pseudo R^2 (0.014), and insignificant p-value (0.995) of the likelihood ratio show that covariates are balanced across the two groups of farming households. The common support graphing (Fig. 2) also shows that there is substantial overlap between adopters and non-adopters of row planting technology.

The imbalance between row planters and broadcasters in terms of the propensity score amounts to more than 65% before matching. However, the bias was significantly reduced to below 4% after matching. As portrayed in the balancing test, before matching, several variables show significant differences, while after matching they are balanced. The covariate balancing indicators such as low pseudo R^2, insignificant p-value of the likelihood ratio test and the mean standardized bias (which is well below 20%) support the hypothesis that row planter and broadcaster farming households have the same distribution in covariates after matching.

5.3. Estimation of treatment effects

The effect of row planting technology for Quncho teff producing farming households on per capita consumption expenditure and crop income per hectare is estimated using three alternative matching algorithms and ATT is compared among these algorithms. The matching techniques are nearest neighbor matching (with replacement), kernel and radius matching. Bootstrap standard errors based on 100 replications are used.

All three matching algorithms showed that adoption of row planting technology had a positive and significant effect on per capita consumption and crop income. Table 3 shows the estimation of average treatment effects on the treated (ATT) from the three matching algorithms. The outcome variable is log of per capita consumption.[12] The increase in per capita consumption ranges from 12.3% to 18.4% higher for row planting households compared with broadcasters. This is the average difference in per capita consumption of similar farming households that belong to different treatment status (users of row planting and broadcasters). Alemu et al.(2014) also found that row planting resulted in almost 14% higher wheat yield than broadcasting method in the high land area of Ethiopia. On the other hand, our findings is in contrast to the findings by a recent study by Vandercasteelen et al. (2018) who found that row planting did not significantly increase teff yield.

Table 3
Estimation of ATT: Effect of row planting of Quncho teff variety on per capita consumption.

	Nearest neighbour	Radius (0.1)	Kernel
ATT	18.4	12.3	13.4
SE	(0.07)***	(0.053)***	(0.057)***
Treated	104	104	104
Control	54	122	122

*** denotes significance level at 1%.

Although the three matching algorithms based on the logit model produced somewhat different quantitative results, the qualitative findings are similar. The results in Table 3 indicate that the adoption of row planting of Quncho teff varieties has a positive and significant impact on per capita consumption expenditure. Using different matching algorithms, the effect ranges from 12.3 to18.4. The increasing impact of the row planting technology thus helps the users of the technology to reduce their consumption poverty. Similarly, Table 4 shows that the row planting technology has a positive and significant effect on crop income per hectare. The treatment effect ranges from ETB1323.1 to ETB 2116.5 higher crop income for the adopters compared to the non-adopters of the row planting technology. This particular finding on crop income is consistent with the findings by Minten et al. (2013), which indicated a positive impact of row planting on yield of the crop.

Results from Tables 3 and 4 suggest that adoption of climate smart practices can help farmers increase their income and reduce food insecurity.

Tables 5 and 6 give the results of the Rosenbaum bounds sensitivity analysis. Matching estimators are not robust against hidden bias. Since estimating the magnitude of selection bias with non-experimental data is not possible,we address this problem through a method proposed by Rosenbaum(2002). Rosenbaum(2002) proposed the Rosenbaum bounding approach in order to check the sensitivity of the estimated ATT with respect to deviations from the CIA.

Based on the results reported in both Tables 5 and 6, we can conclude that the ATT estimates are a pure effect of adoption of row planting.

The results from semi-parametric LIV are reported in Appendix 1. The findings are similar to the propensity score matching, with positive average treatment effects. In addition, the marginal treatment effect is increasing with higher propensity of households to join the treatment status, i.e., row planting.

[12] The log of per capita consumption per adult equivalent is used for the normality of the outcome variable.

Table 4
Estimation of ATT: Effect of row planting technology of Quncho teff variety on crop income per hectare.

	Nearest neighbour	Radius (0.1)	Kernel
ATT	2116.5	1323.1	1540
SE	(916.75)**	(760.5)**	(673.19)**
Treated	104	104	104
Control	54	122	122

** denotes significance level at 5%.

model also show that the marginal treatment effect on crop income is increasing with higher propensity to adopt the row planting technology.

In addition, the majority of sample farming households use row planting technology primarily due to its role in enhancing productivity, absence of lodging (plants falling over), and lower seed rate. However, lack of awareness about the technology and its time consuming nature are the main constraints on the adoption of row planting technology. Any effort to further promote the technology needs to increase awareness and help farm households understand the overall benefit of such technologies. In order to scale up the adoption of row planting, there is a need to improve the extension approaches. Though farmers know the benefit of row planting, farmers are complaining about lack of row planters (Food and Agriculture Organization (FAO, 2016). Therefore, the development of appropriate row planters and its dissemination will enhance the productivity of both land and labour (Vandercasteelen et al., 2014)and hence speed up the adoption of row planting practice.

Table 5
Result of sensitivity analysis using Rosenbaum bounds for log of per capita consumption.

Rosenbaum bounds for log of consumption expenditure (N = 260 matched pairs)						
Gamma	Sig + upper bound significance level	Sig- lower bound significance level	t-hat + upper bound Hodges-Lehman point estimate	t-hat- Lower bound Hodges-Lehman point estimate	CI + upper bound confidence interval (a = .95)	CI-Lower bound confidence interval (a = .95)
1	0	0	8.69926	8.89926	8.66299	8.73492
1.25	0	0	8.67008	8.72693	8.63272	8.76477
1.5	0	0	8.64678	8.75147	8.60915	8.78976
1.75	0	0	8.62671	8.77075	8.58825	8.80999
2	0	0	8.6101	8.7886	8.57063	8.82861

*gamma –log odds of differential assignment due to observed factors.

Table 6
Result of sensitivity analysis using Rosenbaum bounds for crop income per hectare.

Rosenbaum bounds for log of crop income (N = 260 matched pairs)						
Gamma	Sig+- Upper bound significance level	Sig- Lower bound significance level	t-hat + Upper bound Hodges-Lehman point estimate	t-hat- Lower bound Hodges-Lehman point estimate	CI+ Upper bound confidence interval (a = .95)	CI-Lower bound confidence interval (a = .95)
1	0	0	7466.67	7466.67	6933.33	8000
1.25	0	0	7120	8000	6400	8400
1.5	0	0	6666.67	8000	6400	8800
1.75	0	0	6400	8533.33	6133.33	9333.33
2	0	0	6400	8800	5866.67	9600

*gamma –log odds of differential assignment due to observed factors.

6. Conclusion and policy implications

The relationship between climate-smart agricultural practices and the welfare of rural farming households is complicated and there is scant empirical evidence. Though the positive effect of agricultural technology on welfare is widely accepted, assessing the impact of agricultural technology adoption at the micro level is challenging due to the difficulties in finding appropriate methods to quantify the impact of agricultural technologies. This study tries to assess the contribution of row planting technology to the welfare of rural households as measured by per capita consumption expenditure and crop income using both propensity score matching and a semi-parametric LIV method. Furthermore, we used the Rosenbaum bounds procedure to check the sensitivity of the estimated adoption effect to unobserved selection bias. The study was conducted in one of the teff producing areas of the north western parts of Ethiopia.

The results of the study show that row planting technology has positive and significant impacts on per capita consumption and crop income per hectare of farming households. The estimation of the causal impact using propensity score matching suggests that adopters of row planting have higher per capita consumption and crop income than broadcasting households. The result of the sensitivity analysis shows that the estimated treatment effect is insensitive to unobserved heterogeneity showing that the adoption of row planting is associated with increased consumption expenditure and contribute to reducing food insecurity and poverty. The findings from the semi-parametric LIV

Our findings are generally consistent with similar empirical studies on agricultural technology adoption. Scaling up the technology to other areas could help farmers achieve food security and reduce their vulnerability to the effects of climate change. However, the major constraints to the adoption of such practices need to be addressed. Moreover, the impact of such technologies might be context specific and our findings should not be generalized to every part of rural Ethiopia.

The results of the study generally confirm the potential role of the climate-smart agricultural practice (row planting) for the welfare improvement and resilience of farming communities. Future studies may go beyond cross-sectional data and assess the long run effects of the row planting technology. Farmers undertake several practices simultaneously and modeling row planting with other combination of CSA practices will provide a better picture the profitability of row planting in the area. Finally, the role of biophysical factors and their interaction with the socioeconomic environment needs additional empirical investigation.

Appendix A1

Regression Results: Semi-parametric local insrumental variable (LIV)model

As displayed in Fig. A1 below, the semi parametric LIV regression result shows that the MTE is decreasing in U_T showing that the marginal benefit of adopting the row planting technology is increasing in the propensity of the farmer to adopt the planting technology. The semiparametric LIV model produces the following regression result and marginal treatment effect graph.

The MTE is omitted from the regression table and plotted separately over the range of U_T (the propensity not to adopt) consistent with the marginal effect estimator chosen (0,1). Using semiparametric methods, the MTE is estimated at values that lie within the common support of the first stage estimates of the propensity score as shown in Fig. A2. The ATE is reported in the last row of Table A1 while the MTE estimates are plotted separately in Fig. A1. The semiparametric LIV model shows that row planting has significant positive impact only for the crop income. The MTE of the row planting adoption on the per capita consumption expenditure is insignificant.

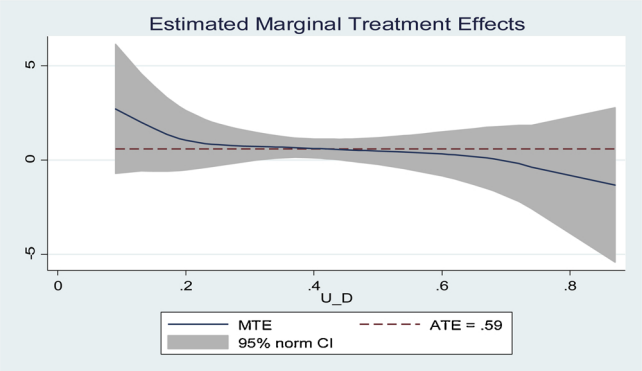

Fig. A1. MTE over the common support of.$P(Z)$

Table A1
Determinants and impact of row planting : Semi-parametric LIV regression.

Parameters	Estimates
Gender	0.7** (0.33)
Age	−0.008 (0.007)
Education	−0.037 (0.03)
Household size	−0.028 (0.1)
Farm size	−0.13 (0.15)
Fertilizer (kg)	−0.0004 (0.005)
Irrigation	−0.33 (0.29)
Access to credit	−0.29 (0.27)
genXp (interaction of gender with pscore)	−1.62* (0.86)
ageXp (interaction of age with pscore)	0.016 (0.22)
educXp (interaction of education with pscore)	0.096 (0.09)
hhsizeXp (interaction of household size with pscore)	−0.01 (0.27)
FarmsizeXp (interaction of farm size with pscore)	−0.1 (0.3)
fert-kgXp (interaction of fertilizer use with pscore)	0.0003 (0.14)
irrigXp (interaction of irrigation with pscore)	0.83* (0.45)
accredtXp (interaction of access to credit with pscore)	0.34 (0.79)
ATE ($E(Y_1 - Y_0)@X$	0.59* (0.33)

Note: The outcome indicator is log of crop income.
*** Significant at 1%.
** Significant at 5%.
* Significant at 10%, (standard error).

Appendix A2 Pearson correlation of wealth indicators and radio ownership

Farm size and radio ownership		
	Farm size	Radio ownership
Farm size	1.00	
Radio-ownership	−0.05	1.00
Significance	0.44	

Livestock ownership (in terms of tropical livestock unit) and radio		
	Tropical livestock unit	Radio ownership
Tropical livestock unit	1.00	
Radio ownership	−0.06	1.00
Significance	0.34	

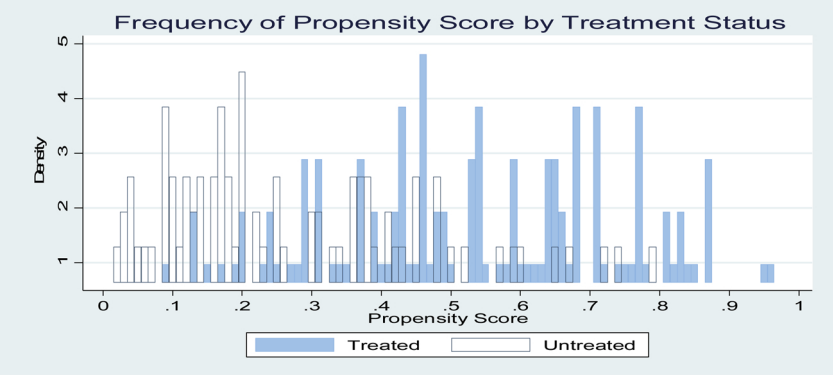

Fig. A2. The common support of P(Z).

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